Marcos da S. Costa, Jadiel C. da Silva, David N. Prata, Marilene A. Mantovani, Kathy C. C. O. Senhorini and Humberto X. de Araujo

Universidade Federal do Tocantins, Brasil

doi:10.15199/48.2020.11.21

A Modified Neural Network for Antennas Optimization

***Abstract**. In mobile communications, devices are generally more compact, nevertheless allow data traffic at high speeds. To meet such demand, embedded hardware must present limited dimensions and at the same time be robust enough to ensure high communication speeds. In this work, a modified Hopfield neural network was applied in the optimization of planar antennas. The role of the algorithm presented here, is to find the ideal antenna dimensions to meet the future 5G mobile technology. With this, a significant improvement in resonance, gain and directivity was expected, which are some of the important parameters in antenna analysis. In the literature, no reference was found based on the modified Hopfield neural network applied to the optimization of planar antennas, which further enhances this research, providing an important and unprecedented contribution. The analysis of the results shows the efficiency, robustness, precision and reliability of this approach, encouraging further research in this area.*

***Streszczenie.** W pracy przedstawiono zmodyfikowaną sieć neuronową Hopfielda wykorzystaną do optymalizacji planarnej anteny. Rolą algorytmu jest znalezienie wymiarów anteny tak aby można było projektować anteny 5G. Doatkowo można antenę optymalizować pod kątem wzmocniania w rezonansie I kierunkowości. (**Zmodyfikowana sieć neuronowa do projektowania I optymalizacji anten**)*

Keywords: planar antennas, 5G. artificial neural networks. hopfield networks. antennas optimization.
Słowa kluczowe: antena planarna, sieć 5G, sieć neuronowa, optymalizacja.

Introduction

Due to the increase in the use of mobile data and the excessive search for a better quality of service, there was a need to develop new technologies, encouraging research on 3G and 4G technologies in the last 10 years [1]. The fourth generation of mobile communication can meet the current demand, however, the number of devices to come along with the Internet of Things (IoT) implementation causes concerns in mobile communication networks, predicting a number of close to 28 billion devices simultaneously connected.

In addition to the challenge of meeting the demand of devices, the 5G technology has the duty to offer a superior quality of service to the current generation of mobile communications, which requires more connection speed, lower latency rate, interference reduction and greater bandwidth [2]. It is estimated that the fifth generation will be able to achievespeed data rates 100 timeshigher than current 4G technology, reaching values between 1 and 10Gbps, which demands greater capacity of microelectronic front-ends and planar antennas [3].

The planar antenna of F-invertedhas earned destade since its initial proposal [4], applied to the structures and techniques of operation in broadband and in multiple frequencies, being still today one of the most used and studied of the literature due mainly, to size, versatility and narrow profile [5].

Recently the researches to achieve a better optimization of planar antennas has been increasing exponentially by the several advantages that they have. These researches have brought some advances in antennas of 3G and 4G technology. In addition, the research of planar antennas in the area of mobile communications is strongly encouraged to reduce its dimensions by adding performance characteristics. In this way, the main objectives of the works in this area are the construction of antennas that are of small size, light, compact, narrow profile, robust and flexible [6-8].

With the increasing of researches exploring methods and alternatives of inherently parallel and adaptive processing architectures, this paper proposes an approach of an Artificial Intelligence based on the Modified Holpfield Artificial Neural Network applied to solving constrained nonlinear optimization problems of a planar antenna for the next 5G technology. The Artificial Neural Network (ANN) is a system capable of performing information processing, with performance characteristics based on biological neural networks with computational capacity acquired through learning and generalization [9]. Therefore, ANN is a promising approach that can be applied efficiently, robustly and accurately in optimization problems of planar antennas.

Antenna Design

Antennas are structures or systems used to radiate or receive electromagnetic signal. They are a very economical device to send information over long distances, making it an indispensable tool in the current communications of cell phones, satellites, mobile devices, computers, among other applications [10].

The main types of antennas currently used are:

Linear antenna: According to the format, are called dipole, monopole, helical and frame. They are of the most common type present in systems of cars, buildings, boats, airplanes, etc [11].

Opening antennas: Because of their ease of installation, they are commonly used in aviation systems. Its formed is cylindrical or conical (pyramidal)[10].

Antenna with reflector: The most common model of this type of antenna is the parabolic reflector model in which the reflecting structure contributes to the elevation of directivity in the irradiation and has great application in satellite links[12].

Planar antenna: Because of its small size and physical profile, it has great application in the microwave range. By its nature, show some advantages when compared to the conventional microwave antennas. The main advantages are related to their design, i.e., they are light, thin and can easily take sizes suited to mobile devices, including ones for the next fifth generation - 5G [13]. Furthermore, it does not require complex in their manufacture, resulting in a low cost antenna. The planar antenna can be easily implemented in integrated circuits and microwave power lines so as impedance matching can be manufactured simultaneously with the antenna structure [14].

The UWB - Ultra Wideband antenna, has as main characteristic the possibility of high data transmission rate. So, it can attend several applications, such as radar, military, commercial, medical systems and in mobile communications devices. To transmit high data rates, a wide bandwidth is essential to avoid interference in the transmission, but the bandwidth is a limiting factor of planar antennas. In this context, an algorithm based on the Hopfield neural network was used to optimize a patch antenna for the next 5G mobile communication system.

Modified Hopfield Network

J. HOPFIELD of the California Institute of Technology along with D. TANK, an AT & T researcher, won the Nobel Prize for developing a large number of ANN models based on fixed weights and adaptive activations, being used as self-learning memories to solve restricted optimization problems[15].

Thus, Hopfield ANN was considered as a dynamic system composed of a determining number of equilibrium states, so that the system will invariably evolve to one of these states from an initial condition and the location of these equilibrium states is controlled by intensity of ANN connections (weights). Moreover, in [16], it is shown that such states of equilibrium can be used as memory devices, unlike those used by conventional computers, in which access to the stored information is given through an address.

Basic Structure

According to [16], and as can be seen from Figure 1, the Hopfield networks are single layer networks with feedback connections between nodes.

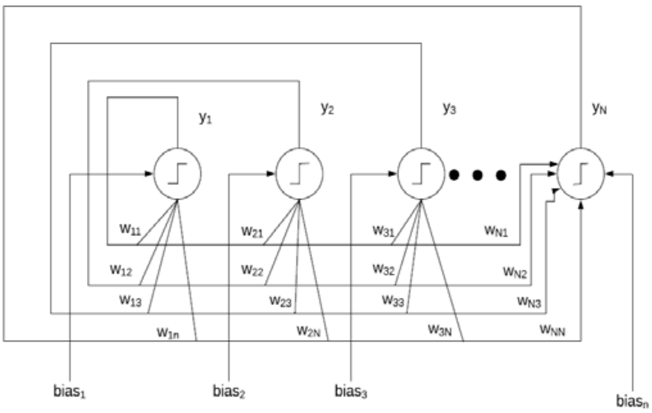

Fig. 1: Schematic of a Hopfield modified neural network.

Thus, the continuous nodal equation in time for a Hopfield network with n-neurons is given by:

(1) $$\dot{u}_i(t) = -\eta.u_i(t) + \sum_{j=1}^{n} T_{ij}.v_j(t) + i_i^b$$

$$v_i(t) = g(u_i(t))$$

where: $u_i(t)$: the current state of the i-th neuron; $\eta.u_i(t)$: the passive decay term; T_{ij}: connection weight between the i-th and j-th neuron; $v_j(t)$: output of the j-th neuron; i_i^b: input vector of the i-th neuron (offset bias) and $g(u_i(t))$: activation function of each neuron.

Equation (1) shows an increasing monotonous activation function, responsible for imposing the threshold at the output of each neuron for a predefined interval. In [17] show that if T is symmetric and $\eta = 0$, the equilibrium points of the network correspond to the values of *v(t)* that minimize the energy function associated with the network (Lyapunov function), and this energy function is defined as:

(2) $$E(t) = -\frac{1}{2}v^T(t).T.v(t) - v^T(t).i^b$$

Using the second method of Lyapunov, it is possible to demonstrate the asymptotic stability of the network, that is, the system dissipates energy over time, where the partial derivatives of the equation 2 are non-increasing, condition that will be reached when the matrix T is symmetric.

In this way, the mapping of the multiband antennas optimization problem through the Hopfield Network is done by determination of the weight matrix T (symmetric) and the vector i^b, to obtain the network equilibrium points that correspond to the optimal solutions of the problem. Thus, the modified energy function will be [18]:

(3) $$E^m(t) = E^{conf}(t) + E^{ot}(t)$$

Operation mode

First, the mode of operation of the modified Hopfield network consists of two phases of minimization of $E^m(t)$of the modified Holpfield network. The first stage consists in minimizing the term $E^{conf}(t)$ where $E^{conf}(t)$ is the confining term of *v(t)* for a valid subspace that groups the structural constraints imposed by the multiband antennas optimization problem, given by [19]:

(4) $$E^{conf}(t) = -\frac{1}{2}v(t)^T.T^{conf}v(t) - v(t)^T.i^{conf}$$

where: *v(t)*: network exit, T^{conf}: matrix of weights, i^{conf}: vector of entries belonging to E^{conf}.

The second phase consists of the minimization of the term $E^{ot}(t)$, which is the optimization term that leads the network output to the equilibrium points, given by [20]:

(5) $$E^{op}(t) = -\frac{1}{2}v(t)^T.T^{op}v(t) - v(t)^T.i^{op}$$

According to [19], the networks equilibrium points, corresponding to the values of *v* that minimize the energy function E^{conf} given by Eq. (4), all belong to the same subspace, named as subspace-valid solutions, determined by:

(6) $$v(t+1) = T^{val}.v(t) + s$$

where: T^{val} is a projection matrix ($T^{val}.T^{val} = T^{val}$) which projects the vector *v* into the valid subspace ($v^{val} = T^{val}.v$), where v^{val} is the component of *v* projected onto the subspace-valid, so the component of *v* will be neglected when it is orthogonal to $T^{val}.v$ and *S* is a vector that is related to the constraints of the multiband antenna optimization problem that will be solved ($T^{val}.s = 0$).

The mode of operation of the Modified Hopfield network consists of the following three main steps [19] and [21]:

I - Minimization of E^{conf}that corresponds to the projection of *v(t)* in the subspace-valid defined by [22]:

(7) $$v(t+1) = T^{val}.v(t) + s = T^{conf}.v + i^{conf}$$

This operation performs an indirect minimization of $E^{conf}(t)$, ie, $T^{conf} = T^{val}$ and. $i^{conf} = s$.

II - Application of a 'non-linear ramp-symmetric' activation function restricting *v* within a hypercube by [16]:

(8) $$g_i(v_1) = \begin{cases} lim_i^{inf}, if \ \ lim_i^{inf} > v_i \\ v_{i,} \quad if \quad lim_i^{inf} \leq v_{i,} \leq \ \ lim_i^{sup} \\ lim_i^{sup}, if \quad v_{i,} > \ \ lim_i^{sup} \end{cases}$$

where $v_i(t) \in \left[\lim_i^{inf}, \quad \lim_i^{sup}\right]$.

III - Minimization of E^{op} will be the update of *v(t)* in the direction of an optimal solution corresponding to the network equilibrium points, that is, will be the update of to obtain the solution of the multiband antennas optimization problem.

In this way, the successive application of the above steps mentioned, will cause the network output to be brought to the equilibrium point that corresponds to the optimum solution of the multiband antennas optimization problem.Then, the mapping of dynamic programming problems through the Modified Holpfield network, consists of obtaining the matrices of weights T^{op} e T^{conf}, and the vectors i^{op} and i^{conf} [16].

Patch Antenna and the Hopfield Network

The optimization of planar antennas is based on the analysis of some factors derived from antenna theory and the principles of neural networks. These factors are discussed and analyzed through logic implementations with the aid of computers.The implementation uses the objective antenna data, which in this case is the planar antenna where its patch has the rectangular shape.

In addition to observing the dimensional characteristics of the antenna, it was defined the application of the same, the future mobile 5G technology, with center frequency around 26 GHz, built in the substrate Rogers Duroid 5880 [23]. From the equations presented in [17]:

$$Ereff = \frac{Er+1}{2} + \frac{Er-1}{2}\left[1+12\frac{h}{W}\right]^{-1/2} \tag{9}$$

$$W = \frac{Vo}{2\,fr}\sqrt{\frac{2}{Er+1}} \tag{10}$$

$$\Delta L = 0.412h\frac{(Ereff+0.3)\left(W/h+0.264\right)}{(Ereff-0.258)\left(W/h+0.8\right)} \tag{11}$$

$$L = \frac{Vo}{2\,fr\sqrt{Ereff}} - 2\Delta L \tag{12}$$

The table 1 show the results of the solution of these equations results in the width and length dimensions of the designed antenna.

Table I: Typical Antenna Dimensions through the proposed equations.

Parameters	Dimensions
W	4.56 mm
L	3.56 mm
$\Delta L/h$	0.514688
E_{reff}	1.9925
ΔL ΔL	0.2614mm

The neural network used in this work is the Modified Hopfield Network, found in [14]. To apply the Modified Hopfield network with the objective of optimizing the planar antenna, it was necessary to use existing theory for planar antenna design through the aforementioned equations and to couple this theory to experiments made by repeated simulations in the CST. When evaluating the output signal by comparing it with predefined parameters, characteristic features of the system can be obtained for the problem situation. The sample data are obtained by simulation, i.e., it is necessary for the effectiveness of the network, simulated samples in the CST and its response.

The methodology used to configure the network can be splited into three parts [24]. First, the algorithm defines the existing equations for the definition of antenna dimensional parameters, so the algorithm returns the data and defines the hypercube constraints for the network(Hopfield and Tank, 1985):

$$\begin{cases} S11_{ot} < -10dB \\ S11_{ot} < S11_t \\ a * L_t < L_{ot} < b * L_t \\ c * W_t < W_{ot} < d * W_t \end{cases} \tag{13}$$

The first restriction is the consideration that represents the maximum return loss that the antenna can present. The second restriction indicates antenna optimization, telling the program to return only dimensional brackets that generate an antenna with features optimized over the typical antenna. The third and fourth constraint is malleable, that is, a variation around the point is defined that is equivalent to the typical antenna data, and this variation is controlled with constants a, b, c, and d.

The second part of the algorithm, refers to network processing. For this, it is used the sample data that were obtained from the simulations in the CST and with these data constants that form a characteristic equation of the antenna, given by equation 14:

$$f(x_i) = \sum_{i=1}^{n} a_i . x_i \tag{14}$$

The variable x_i represents the antenna dimensions, and the constant a_i represents the weights of the neural network. From this equation the neural network analyzes the hypercube and calculates for every possible point a value f that represents the antenna factor S11, and verifies the limitations imposed by hypercube, if these limitations are accepted, both the result f and the associated dimensions are stored in the response vector R [25].

The last part of the algorithm refers to the network feedback [26]. When the response in R is stored, the algorithm replaces the condition of two, which states that parameter S11 must be larger than that of the typical antenna, to be larger than S11 found by the network, and continues to analyze the hypercube until it has processed all possibilities within the hypercube. With this, at the end of the processing the neural network, will have stored in R, the optimized value of the network [16].

Results

The proposed antenna designed here, was built in Rogers RO4003 substrate with ε_r = 3.55 and thickness of 0.81 mm. The copper layer has 0.035 mm of thickness. The dimensions of the fabricated UWB antenna are shown in Fig.1. The ground plane has a hole with height of 1 mm and width of 4 mm, symmetrically located.

Therefore the constraints are malleable from the constants a, b, c and d. By varying these constants, two optimized antennas were obtained from each other.The first antenna was named Type A optimized antenna and the second Type B optimized antenna.

The rectangular antenna chosen has several dimensions that influence the characteristics of the antenna. The dimensions W, L, Wg and Lg were defined, since they are the base dimensions of the antenna. First, the parameters of the typical antenna were obtained, with equations (9), (10), (11) and (12). The dimensions found were:

Table 1: Typical Antenna Dimensions

	W(mm)	L(mm)	Wg(mm)	Lg(mm)
Optimized Antenna ‘A’	4.56	3.56	6.11	4.770

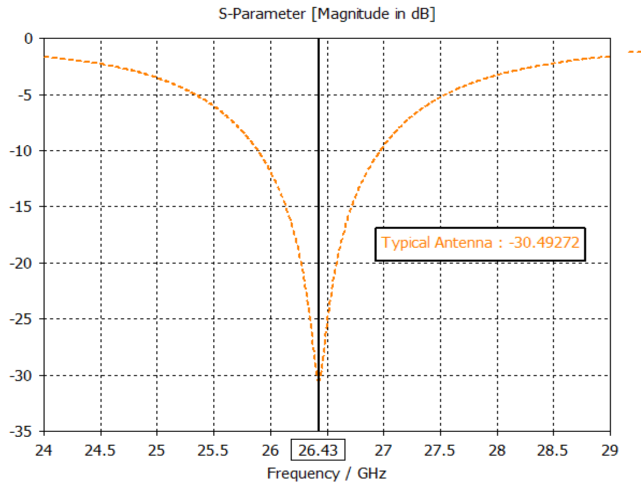

Fig. 2: Parameter S11, Typical Antenna

The typical antenna shows in Figure 2 that the frequency of higher resonance is 26.43GHz.At this point, the antenna has -30.50dB and a bandwidth of 1.1GHz. Analyzed these initial data, when applying the neural network, the following results were found for the dimensional parisons in the Optimized Antenna Type A:

Table 3: Dimensions Antenna Type A

	W(mm)	L(mm)	Wg(mm)	Lg(mm)
Optimized Antenna A	4.37	3.56	6.09	4.498

With these dimensions was simulated in the CST MICROWAVE STUDIO®, and obtained a return loss response of:

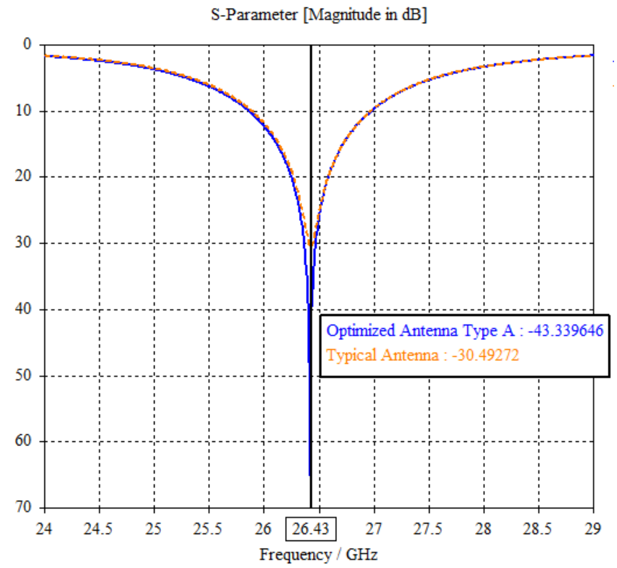

Fig.3: Parameter S11, Typical Antennas and Type A

Figure 3 shows that there was an improvement over the return loss, where the Type A antenna obtained a return loss of -43.43dB at the same frequency as the typical antenna, this response represents a 42.39% improvement over the typical antenna.That is, this antenna has a signal loss 42.39% lower than the typical antenna.In terms of bandwidth, both antennas have 1.1 GHz widths, and there is no change due to the algorithm.

The optimized antenna presented improvements in all the characteristics, mainly in relation to the loss by return, defining it as satisfactory.The other antenna found, was the Type B antenna, for this antenna the following dimensional characteristics were obtained:

Table 4: Antenna Type B Dimensions

	W(mm)	L(mm)	Wg(mm)	Lg(mm)
Optimized Antenna B	4.35	3.56	6.09	4.770

With these dimensions, a return loss of Type A antenna as compared to a Typical antenna in Figure 4, we can see that the typical antenna has a maximum resonance at 26.43 GHz, -30.50 dB and the Optimized Type B antennaat this same frequency has a resonance of -43.34 dB, where it shows an improvement of 42.1%.Regarding the bandwidths, both antennas presented approximately one band of 1Ghz. Considering a small difference in frequency, the type B antenna had a maximum resonance of -65dB at 26,418Ghz, which shows an improvement of 113% over the typical antenna.

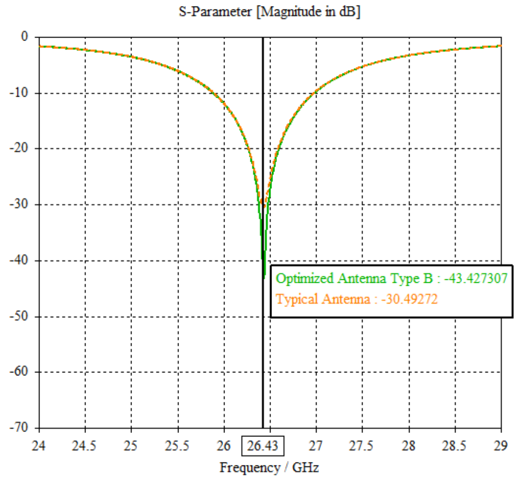

Fig. 4: Parameter S11, Typical Antennas and Type B

Conclusions

Both antennas presented significant results, it is observed that all the antennas presented a bandwidth of approximately 1 GHz. In relation to the typical antenna resonance frequency both antennas had a return loss of approximately -43dB, but in the vicinity of this frequency, at exactly 26.418GHz, the type B antenna showed a significant improvement of 113% in relation to the typical antenna, making it in relation to the other two, the antenna with the characteristic improvement.

As a future objective, this algorithm is perfected, where it is possible and effective to implement it for the various existing antennas and thus optimize them for future mobile telephony technologies, as well as for other application areas of the planar antenna.

Authors

M. S. Costa, Faculdade de Engenharia Elétrica, Universidade Federal Tocantins, Av: NS 15 ALC NO 14, 109 Norte - 77001-090, Palmas - TO, Brazil email: marcos.sicos@yahoo.com

Prof. J. C. da Silva, Faculdade de Engenharia Elétrica, Universidade Federal Tocantins, Av: NS 15 ALC NO 14, 109 Norte - 77001-090, Palmas - TO, Brazil email: jadiel@mail.uft.edu.br

Prof. D. N. Prata, Modelagem Computacional e de Sistemas, Universidade Federal Tocantins, Av: NS 15 ALC NO 14, 109 Norte - 77001-090, Palmas - TO, Brazil email: ddnprata@gmail.com

Prof. M. A. Mantovani, Faculdade de Engenharia Elétrica, Universidade Federal Tocantins, Av: NS 15 ALC NO 14, 109 Norte - 77001-090, Palmas - TO, Brazil email: marilene.mantovani@mail.uft.edu.br

Prof. K. C. C. O. Senhorini, Faculdade de Engenharia Elétrica, Universidade Federal Tocantins, Av: NS 15 ALC NO 14, 109 Norte - 77001-090, Palmas - TO, Brazil email: kathy@mail.uft.edu.br

Prof. H. X. Araujo, Modelagem Computacional e de Sistemas, Universidade Federal Tocantins, Av: NS 15 ALC NO 14, 109 Norte - 77001-090, Palmas - TO, Brazil email: hxaraujo@uft.edu.com

REFERENCES

[1] Pierucci, L. (2015) The Quality of Experience Perspective Toward 5G Technology. Proceedingsof IEEE Wireless Communications, 4(22); pp. 10-16.

[2] Osama, M. H., Ayman, E. and Abdel-Razik S. (2014) New dense dieletric patch array antenna for future 5G short-range communications. Proceedings in 16th International Symposium on Antenna Technology and Applied Electromagnetics(ANTEM), Victoria, BC, Canada. July 13-16; pp 1-4.

[3] Kabalci Y. (2019) 5G Mobile Communication Systems: Fundamentals, Challenges, and Key Technologies. In: Kabalci E., Kabalci Y. (eds) Smart Grids and Their Communication Systems. Energy Systems in Electrical Engineering. Springer, Singapore, pp. 329-359

[4] Fujimoto, K. and James, H., (1987) Small Antennas. John Wiley & Sons:Research Studies Press, United Kingdom.

[5] Zhai, W., Miraftab, V., Repeta, M. (2015) Broadband antenna array with low cost PCB substrate for 5G millimeter wave applications. Proceedings of Global Symposium on Millimeter-Waves (GSMM), May 25-27; pp 978-980.

[6] Garg, R. and Bahl, I. (2001) Microstrip Antenna Desing HandBook. Artech House, Norwood, United Kingdom.

[7] Chen, Z. N. andChia, M. Y. (2006) Broadband Planar Antennas: design and applications.John Wiley & Sons, Chichester, United Kingdom.

[8] Wong, K. L. (2002) Compact and Broadband Microstrip Antennas. John Wiley & Sons, Inc. New York, United States of America.

[9] Braga, A.P.,Carvalho, A. C. P. L. F. andLudemir, T. B. (2007) Redes Neurais Artificiais: teoria e aplicações. 2nded. Rio de Janeiro: LTC, Brazil.

[10] Fujimoto, K. and Morishita, H. (2013) Modern Small Antennas. Vol. 1, Cambrige University Press, New York, United States of America.

[11] Mandal D., Kar R., Bandyopadhyay S. (2019) RGA-Based Wide Null Control for Compact Linear Antenna Array. In: Bhatia S., Tiwari S., Mishra K., Trivedi M. (eds) Advances in Computer Communication and Computational Sciences. Advances in Intelligent Systems and Computing. Springer, Singapore. 759, pp. 269-280.

[12] Balanis, C. A. (2016) Antenna theory: analysis and design.4thed. New Jersey: John Wiley& Sons, Inc. United States of America.

[13] Boccardi, F., Heath, R. W., Lozano, A., Marzetta, T. L. and Popovski, P. (2014) Five Disruptive Technology Directions for 5G. Proceedings of IEEE Communications Magazine, 2(52). February; pp 74-80.

[14] Silva, I. N., Amaral, W. C. and Arruda, L. V. R. (2004) Uma abordagem usando redes neurais artificiais para resolução de problemas de otimização restrita. Pesquisa Operacional. 24(2), pp. 285-302.

[15] Hopfield, J. J. (1982) Neural networks and physical systems with emergent collective computational abilities. Proceedings of the National Academy of Sciences. 79, pp. 2554-2558.

[16] Hopfield, J. J. and Tank, D. W. (1985). Neural computation of decisions in optimization problems. In Biological Cybernetics. 52(3), pp. 141-152.

[17] Tank, D. W. and J. J. Hopfield (1986). Simple neural optimization networks: an A/D converter, signal decision network and a linear pro-gramming circuit.In IEEE Transaction on Circuits and Systems. 33(5) pp. 533-541.

[18] Silva, I. N., Goedtel, A. and Flauzino, R.A., (2007) The Modified Hopfiled Architecture Applied in Dynamic Programming Problems and Bipartite Graph Optimization. International Journal of Hybrid Intelligent Systems 4, pp. 17-26.

[19] Aiyer, S.V.B., Niranjan, M. and Fallside, F. (1990) A theoretical investigation into the performance of the hopfield network.In IEEE Transaction on Neural Networks. 1(2), pp. 204-215.

[20] Silva, I. N., Souza, A. N. and Ulson, J. A. C. (2001) A Modified Hopfield Model for Solving Several Types of Optimization Problems. In: Cihan H. Dagli; Anna L. Buczak. (Org.). Intelligent Engineering Systems ThroughArtificial Neural Networks. 1st ed. New York, USA: ASME Press. 11, pp. 897-902.

[21] Silva, I. N., Amaral, W. C., and Arruda, L. V. R. (2005). Design and analysis of efficient neural network model for solving nonlinear optimization problems, International Journal of Systems Science. 28(13), pp. 833-843.

[22] Liang, X. B. andWang, J.,(2000) A recurrent neural network for nonlinear optimization with a continuously differentiable objective function and bound constraints. In IEEE Transactions on Neural Networks 11(6)pp 1251 – 1262.

[23] Medeiros, T. E. de L., (2013) Antenas de microfita sobre substrato dielétrico organizado de forma quase periódica. Masters dissertation in Communication and Automation Systems. Federal Rural University of the Semi-Arid (UFERSA), Mossoró (RN) Brazil.

[24] Kennedy, M. P. and Chua, L. O. (1988) Neural Networks for Nonlinear Programming. In IEEE Transaction Circuits Systems.35(5) pp 554-562.

[25] Vidyasagar, M. (2002) Nonlinear Systems Analysis: Second Edition. Prentice-Hall, Englewood Cliffs (NJ), United States of America.

[26] Luenberger, D. G. (1984) Linear and Nonlinear Programming. 2nd ed: Addison-Wesley.